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I, David Jones, hereby submit this original work as part of the requirements for the degree of Doctor of Education in Counselor Education.

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Postnatal depression (PND) and neighborhood effects for women enrolled in a home visitation program

A dissertation submitted to the Graduate School of the University of Cincinnati in partial fulfillment of the requirements for the degree of Doctor of Education in the Counseling Program of the College of Education, Criminal Justice, and Human Services

by

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Abstract

Postnatal depression (PND) impacts an estimated 13% of women of childbearing age. PND impacts the mother’s offspring evidenced by increased risk of developmental delays, alcohol dependence, anxiety, and depression. Many investigators have examined the individual risk factors associated with PND but only a few studies outside of the U.S. have delved into the maternal neighborhood characteristics for PND. The aim of this study was to investigate the association between postnatal depression potential and structural neighborhood characteristics among at-risk women in a home visitation program in Hamilton County, Ohio. The archival data sources - eECS (individual level) and U.S. 2010 census tract (neighborhood level) were utilized for this study. The sample included 295 mothers enrolled in a home visitation program between 2006 and 2011 who were at risk for developing PND, observed as three-month Edinburgh Postnatal Depression Scale (EPDS) scores ≥ 10. After a principal component analysis of the structural characteristics, two components were maintained: Social Disadvantage and Stability. These two components were the neighborhood predictors analyzed in a generalized estimating equation (GEE) method using clustered standard errors. Stability was negatively associated with PND potential. Social Disadvantage was not found to be statistically significantly associated with PND potential. The findings suggest that women in home visitation programs who have high EPDS scores and live in unstable neighborhoods are at special risk of developing PND. This finding is significant in that it is possible for the counseling profession to intervene with at-risk women not only at the individual level, through differing therapeutic approaches (individual to group), but also at the neighborhood level (e.g., advocating for policy to increase stability).
Keywords: postnatal depression, neighborhoods risk factors, social determinants of health, generalized estimating equations
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CHAPTER 1 - Introduction

Statement of the Problem

In the United States, many people know about or have experienced depression. Yet few may have heard of or experienced postnatal depression (PND), a specific type of depression that women experience after the birth of a child and up to the first year of the child’s life (Abbasi, Chuang, Dagher, Zhu, & Kjerulff, 2013; O’Hara & McCabe, 2013). Postnatal depression impacts an estimated 13% of women of childbearing age in the United States (Leigh & Milgrom, 2008). When experiencing PND, women often describe having difficulty in memory, concentration, loss of appetite, anxiety, depressed mood, and sleeping difficulties (The American College of Obstetrics and Gynecology, n.d.). When left untreated, PND may not be self-limiting and may contribute to postnatal psychosis (Bennett & Sylvester, 2013). A meta-analysis has identified low self-esteem, strained marital status, stressful life events, a history of maternal depression, anxiety and depression during pregnancy, inadequate social support, neuroticism, poverty, race, unemployment, poor general health, low educational status, birthing complications, and young maternal age as risk factors associated with PND (O’Hara & McCabe, 2013). Though many have identified the individual level risk factors associated with PND, scant studies have examined the association of a mother’s neighborhood with her risk of PND.

Postnatal Depression, Impact on Mother’s Children

Maternal depression is associated with adverse outcomes among offspring. The first signs occur in-utero and are associated with low birth weight, premature birth, and irregular fetal heart beat (Hubner-Liebermann et al., 2012). Another path is through impaired caretaking by the mother (Wang, Wu, Anderson, & Florence, 2011). These progeny exhibited irritability,
developmental delays, and somatic concerns. Within the dyad, the infant exhibits dismissive behaviors towards mother. Outside of the dyad, the infant interacts less with others and is fearful towards strangers. Finally, these children are more likely to develop mental disorders in adolescence such as depression, anxiety, and alcohol dependence (Zajicek-Farber, 2008).

A Mother’s Neighborhood and Her Risk of Postnatal Depression

Historically, depression has been the main outcome when examining neighborhood effects. Structural neighborhood characteristics that have been associated with depression are neighborhood poverty, neighborhood cohesion, poor quality housing, low neighborhood socioeconomic status (SES), availability of a car for transportation, low household income, residential stability, and built environment conditions such as walkability (Mair, Roux, Galea, & Arbor, 2008).

To understand the relationship between PND and neighborhood effects, a literature review was conducted. From the literature review, no studies were discovered that examined the neighborhood effects on PND in the United States. Yet, researchers in Brazil and Australia have examined this association. Tannous, Gigante, Fuschs, and Busnello (2008) found a relationship between PND and per capita income in Southern Brazil. In South West Sydney, Australia, a concurrent mixed methods research study was conducted in an effort to develop a social epidemiological theory of PND. The investigators utilized various data collection methods such as focus groups, interviews of maternal and child health professionals, and statistical approaches including exploratory factor analysis, logistic regression, and Bayesian spatial linear regression (Eastwood, Jalaludin, & Kemp, 2014c). From the exploratory factor analysis (EFA), six factors were discovered: social cohesion, neighborhood adversity, maternal health behaviors, housing
quality, access to services, and social capital (Eastwood, Kemp, Jalaludin, & Phung, 2013b; Eastwood, Jalaludin, Kemp, & Phung, 2014a, 2014d; Eastwood, Kemp, & Jalaludin, 2014b). Through these themes, the researchers then examined risk for PND through two outcomes based on the mother’s Edinburgh Postnatal Depression Scale (EPDS) score, EPDS > 9 and EPDS > 12, using a Bayesian spatial linear regression. EPDS > 9 was associated with percent no support, Entropy Index (a measure of community diversity), percent living in apartments, and percent smoking as risk factors associated with PND risk. For EPDS > 12, no support, Entropy Index, and no regret leaving suburb were found to be statistically significant with PND (Eastwood et al., 2014d).

**Purpose of Study**

Evidence clearly suggests that PND negatively impacts the mother, her child, and the relationship between mother and child. Moreover, it is currently understood that group-level factors such as socioeconomic status, built environment, social connectivity, and racial/ethnic composition impact the mental health of individuals living within those communities (O’Campo, P., Salmon, C., & Burke, J., 2009; Eastwood et al., 2014d). Yet, little is known about how neighborhood characteristics may impact PND potential; no peer-reviewed study has been discovered within the United States and only a few studies outside of the United States. Moreover, research has not tested for neighborhood effects among women who are at risk for PND. Not all at-risk women go on to develop PND, but it is not clear if neighborhood characteristics can explain which at-risk mothers do or do not.

The purpose of this study was to examine the structural neighborhood effects on PND potential among at-risk women. To gain a greater understanding of the influence of structural
neighborhood characteristics on PND potential, this study tested for neighborhood effects using
data drawn from women participating in a home visitation program in Cincinnati, Ohio. This
study addressed the question, “What maternal structural neighborhood characteristics predict
postnatal depression potential among at-risk mothers enrolled in a home visitation program?” It
is hypothesized that a mother’s structural neighborhood characteristics, defined by the 2010
United States census tract, will explain a portion of the variance in at-risk mothers’ Edinburgh
Postnatal Depression Scale (EPDS) scores.

**Significance of Study**

Based on the summary above, PND has been examined extensively at the individual
level, e.g., the individual level risk factors that contribute to postnatal depression (O’Campo et
al, 2009). Yet, contemporarily, no peer-reviewed study in the United States was found that
examined neighborhood risk factors for PND, generally, or more specifically for women enrolled
in a home visitation program at risk for PND. The literature suggests that deprived neighborhood
characteristics increase risk of PND (O’Campo, 2009; Eastwood et al., 2014d). Therefore, by
understanding contextual variables, counseling professionals and others might advance social
justice and reduce the prevalence of PND by advocating for changes in neighborhood structures.
This, in turn, could increase overall wellness in the community, but especially in women
identified as at risk for PND, based on a EPDS score greater than or equal 10, who are enrolled
in a home visitation program. Identifying these structural neighborhood characteristics and
advocating for change might, better prevent the possibility of PND for these high-risk women
who are enrolled in a home visitation program.
Definition of Terms

Postnatal depression - maternal depression with an onset within a year after giving birth (O’Hara & McCabe, 2013).

Peripartum depression – depression that is evident in the last month of gestation to the first couple of months after the mother gives birth (Hubner-Liebermann et al., 2012).

Neighborhood - Neighborhoods can be operationalized into two distinct concepts – structural and functional. The structural characteristics of a neighborhood can be defined by characteristics such as quality of housing, percent poor, educational status, racial makeup, and unemployment rate. The functional characteristics of a neighborhood focus on resident behaviors (Cutrona, 2008).

Risk factors – factors that increase the probability that a person will become ill, i.e, smoking cigarettes is a risk factor for lung cancer. A risk factor is a factor that precedes the outcome (AFMC, n.d.; Fontenelle & Hasler, 2008).

Home visitation program – a prevention approach where professionals deliver services in the client’s home. Initially, prevention was aimed in reducing child abuse and neglect but now has expanded services included mental health counseling (Ammerman et al., 2007).

Census tract – a subdivision of a county with a population size ranging between 1,200 and 8,000 and are generally permanent overtime (U.S. Census Bureau, n.d.)
CHAPTER 2 - Literature Review

A literature review on PND will be offered in this chapter. In particular, this chapter will describe a definition for PND, the prevalence of PND, the signs and symptoms associated with PND, the risk factors for PND, the current theoretical conceptualization of PND, and the impact of PND on offspring. Additionally, the literature review will define neighborhood, explain the impact of neighborhood on mental health, and expound on the association of neighborhood characteristics with PND. The etiology of PND will be viewed through a number of theoretical frameworks and current prevention efforts aimed at PND will be surveyed.

This literature review utilized Scopus, EBSCO (PsycINFO, Medline, and Search Complete), Google Scholar, and specific journals - Journal of Counseling and Development, American Journal of Public Health, and Health and Place. The search was not restricted by time. The key terms utilized for the search were “home visitation,” “neighborhood,” “census tract,” “depression,” “maternal depression,” “postpartum depression,” and “postnatal depression.”

**Postnatal Depression**

**Defining Postnatal Depression**

A spectrum exists for maternal depression. The mildest form is postpartum blues. This is followed by PND and then the most extreme experience of maternal depression, postpartum psychosis (O’Hara & McCabe, 2013). The prevalence of postpartum blues has ranged from 26 to 80 percent and occurs within the first 7 to 10 days after a mother gives birth. This experience is typically mild and transient. A peak has been identified between day 3 and 5 postpartum for symptoms associated with a negative mood state. The mood is characterized by swings and excessive sensitivity. An association has been discovered between postpartum blues and PND –
there is an increased risk for PND for mothers who are experiencing postpartum blues (Buttner, O’Hara, & Watson, 2012).

Some suggest that PND can occur “anytime during pregnancy, upon delivery, and up to a year postnatal” (Pearson, 2008, p. 7). Others believe that PND is ill-defined, i.e., no current consensus (Albright, 1993; Cole, 2009). Given this caveat, the DSM IV-TR subsumes PND as a specifier within major depressive disorder (American Psychiatric Association, 2000). Currently, the DSM-5 restricts this phenomenon as a specifier to “with peripartum onset”; this specifier only recognizes during pregnancy and up to 4 weeks (American Psychiatric Association, 2013). Therefore, the time period for postpartum depression continues to be debated. Yet O’Hara and McCabe (2012), in their review of the current status of postpartum depression, suggested that the time frame depends on the research study. For biologically based studies, the time period will be typically shorter, such as in the DSM criteria, but for sociological, treatment, and prevention studies, a longer time period will be utilized for PND.

Postpartum psychosis, also called puerperal psychosis, is a rare disorder occurring in about 0.1 to 0.5 percent of women (O’Hare & McCabe, 2013) or in about 1 in 500 (Cox, Holden, & Sagovsky, 1987). Postpartum psychosis is characterized by a psychotic event several weeks after giving birth. It is an acute incident with a rapid onset. Mothers who have experienced postpartum psychosis have signs and symptoms such as “inability to sleep, confusion, agitation, delusions, hallucinations, severely disturbed mood and behavior and being often out of touch with reality” (Westall & Liamputtong, 2011, p. 10).
Postpartum Depression Prevalence and Features

The risk of maternal depression is the highest within the 1st month. At 6-months the risk is reduced. Around the 36th month and beyond, the risk for depression stabilizes (Wang et al., 2011). The majority of cases occur after delivery. One-fifth or 20% of women are at risk for depression within the first three months following birth. PND is estimated to affect 7 to 20 percent of women (Abrams, Dornig, & Curran, 2009; Amankwaa, 2005; Beck, 2002; Choate & Gintner, 2011; Cole, 2009; Smith & Lincoln, 2011).

When examining the symptoms associated with PND, The American College of Obstetrics and Gynecology (ACOG, n.d.) includes the following as typical symptoms associated with PND: depressed mood, sleeping difficulties, concentration concerns, poor appetite, and noticeable anxiety. Additionally, the symptoms must last for at least two weeks. Outside of the medical model, others have reported signs and symptoms, such as changes in sleeping and eating patterns, “sadness, difficulty in coping, irritability, anxiety, negative thoughts, fear of being alone, loss of memory or confusion, loss of concentration, feeling guilty, loss of self-esteem and/or thoughts of hurting the self or the baby” (Westall & Liamputtong, 2011, p. 2).

Risk Factors Associated with Postnatal Depression

The individual level risk factors have been the most studied. Even with the contested definition, many have investigated the risk factors associated with PND. Through the current study’s literature review, the following risk factors have been identified for PND: low self-esteem, strained marital status, stressful life events, history of depression, anxiety and depression during pregnancy, inadequate social support, neuroticism, poverty, race, unemployment, poor general health, lower educational attainment, birthing complications (pre-eclampsia, emergency
caesarian), infant’s temperament, and young maternal age (O’Hara & McCabe, 2013; Wang et al., 2011). Leigh and Milgrom (2008) have also discovered a mother who has a history of a miscarriage, pregnancy termination, and childhood sexual abuse has an increased risk for PND. Additionally, Gallup, Pipitone, Carrone, and Leadholm (2009) have found an association between bottle-feeding and PND.

Furthermore, a concurrent triangulated mixed methods (MMR) study using critical realist theory was conducted in an effort to establish a social epidemiological theory of maternal depression. The study was a population-based cross-sectional study in South West Sydney, Australia with 29,405 mothers with newborns who completed the EPDS within two weeks of delivery between 2003 and 2004. Initially, by applying principal component analysis and multivariate logistic regression, the researchers identified the following individual-level predictors: mother’s expectation around motherhood, difficult financial situation, foreign-born mother, unplanned pregnancy, not breastfeeding, poor maternal health, limited social and emotional support, demanding baby, baby sleeping difficulties, and baby not content (Eastwood, Phung, & Barnett, 2011; Eastwood, Jalaludin, Kemp, Phung, & Barnett, 2012a). The researchers also attempted to identify latent variables associated with the risk of PND. From a PCA, they discovered five components: Maternal Responsiveness, Social Exclusion, Infant Behavior, Migrant Social Isolation, and Family Size. Using EPDS >12 as the outcome variable and logistic regression, Maternal Expectations, Social Exclusion, Infant Behavior, and Migrant Social Isolation remained in the multivariate model when controlling for the other components (Eastwood, Jalaludin, Kemp, Phung, Barnett, & Tobin, 2012b). Finally, Eastwood, Kemp, & Jalaludin (2015) integrated the qualitative (qual) and quantitative (quan) arms of the study. From
the integration two mechanisms became salient for the investigators: lost maternal expectations and being alone.

PND is correlated with race and ethnicity (O’Hara & McCabe, 2013). Women of ethnic minority status, Black and Hispanic, have an increased risk of PND when compared to White women. Some of this may be explained by income, but there is evidence that low-income minority status women still have an increased risk for PND when compared to their counterparts of European descent (O’Hara & McCabe, 2013). Additionally, the mother’s belief system around depression has been determined a risk factor. For mothers of minority status in the United States, trepidation towards entering into the health care systems has been noted. For example, for African American women, there is a belief of being a strong Black woman – a reliance on self to resolve the issue. Moreover, an overt distrust of the healthcare system and specifically the mental healthcare system has been identified with this population. This belief contributes to an aversion to seeking help within the healthcare system. For women of Hispanic descent, there is a strong stigma around seeking mental health care. Finally, across ethnic minorities, there are religious beliefs that deter seeking help within the mental healthcare setting (Abrams et al., 2009).

Postnatal Depression, Impact on Mother’s Children

There is clear evidence that when a mother experiences PND it disrupts mother and child attachment (Boyd, Zayas, Mckee, 2006; O’Hara & McCabe, 2013). Peripartum depression has been associated with preterm birth, low birth weight, and irregular heart rate (Hubner-Liebermann et al., 2012). One of the most noted outcomes with PND is that a new mother experiences impairment. The mother’s negative state directly impacts her care of her child (and other children in the house) - a ten-fold risk of a poor relationship with her children (Wang, et al,
Additionally, if left untreated, PND may develop into recurring depressive episodes (Goodman, 2011).

One area potentially impacted is breastfeeding. Mothers who experience PND have poor outcomes with breastfeeding; the odds of bottle feeding increases as the EPDS score increases, e.g., less likelihood of breastfeeding to be maintained (Gagliardi, Petrozzi, & Rusconi, 2012). As a cautionary note, others have not found this association (O’Hara, 2013). Besides breastfeeding, other potential detrimental effects have been discovered throughout the child’s development for mothers who experience PND. These include absenteeism to well-child visits, missed child immunizations, and incorrect sleeping position (Zajicek-Farber, 2009).

A few studies have approached interaction of the dyad systematically. Boyd, Zayas, and McKee (2006) conducted a longitudinal study comparing African American mothers to Hispanic mothers. The results were unexpected. No differences were found between the two groups of mothers with higher depressive symptoms in how they interacted with their infant. The only statistically significant difference was that depressed mothers averted their gaze more often than non-depressed mothers. A main study limitation was that clinical depression criteria were not used and women may have been placed in the depressed group but had not met the clinical diagnostic requirements for depression. An additional caveat was this study focused on the perinatal period. Yet others (Pearson et al., 2013; Wisner et al., 2013) have found data countering this conclusion. They discovered a profound disadvantage among depressed mothers and their interactions with their infants. The postnatal period is a time of high dependence of the infant on the caregiver. Depressed mothers have been found to engage in suboptimal caregiving (Pearson,
2013). Also, an association has been documented of maternal depression and preschool problems (Azak, Murison, Wentzel-Larson, Smith, Gunnar, 2012).

Goodman, Rouse, & Connell (2011) conducted a meta-analysis of 193 studies examining strength of the association of adverse child outcomes and maternal depression. Through this meta-analysis, they found by the middle of childhood, children of depressed mothers, when compared to children of non-depressed mothers, had increased rates of mood disorders, internalizing problems (depression, anxiety) and externalizing problems (conduct, oppositional, hyperactive, aggression). One of the main predictors was age: the younger the child, the stronger the association (Goodman et al., 2011).

Finally, children of mothers who experienced PND are more likely to develop mental disorders such as depression, anxiety, and alcohol dependence in adolescence (Zajicek-Farber, 2008). Sanger, Lles, Andrew, & Ramchandani (2014) conducted a systematic review (PsycINFO, Medline, and Embase) probing adolescents who were exposed to PND and their psychological outcomes. They discovered 16 peer-reviewed journals and revealed conflicting evidence to support internalizing and externalizing outcomes and psychopathology. The authors suggested that PND increases the risk of recurrent maternal depression but the recurrent depression may be a stronger predictor for adolescent psychological outcomes.

**Neighborhood and Postnatal Depression**

**Defining a Neighborhood**

Sampson, Morenoff, and Gannon-Rowley (2002) defined neighborhoods as “ecological units nested within successively larger communities” (p. 445). Neighborhoods can be operationalized into two distinct concepts – structural and functional. The structural
characteristics of a neighborhood can be defined by features such as quality of housing, percent poor, educational status, racial makeup, and unemployment rate. The U.S. Census, historically, has been used to define structural neighborhood characteristics in research studies (Cutrona, 2008). The functional characteristic of a neighborhood focuses on resident’s behaviors. This could include positive or negative behaviors of a community that, as a whole, illustrate a pattern. This data is generally assessed through surveys or systematic observation of a neighborhood.

**Neighborhood Impact on Mental Health**

The relatedness of an individual’s environment and their wellbeing has historical precedence. This phenomenon has been studied as far back as 1930s. For example, Faris and Dunham (1939) discovered that substance abuse and schizophrenia were associated with socially disparate or disorganized communities in Chicago, Illinois.

The association between neighborhood characteristics and mental health in adults has been well documented and particularly in depression (Barnes, Belsky, Frost, & Melhuish, 2011; Cutrona, Wallace, Wesner, 2006; Eastwood et al., 2014d, Wainwright, Surtees, 2004; Weich, Twigg, Holt, Lewis, Jones, 2003). Mair, Roux, Galea (2008) conducted a review of published observational studies. This review focused on depression and neighborhood characteristics. They reviewed studies between 1990 and 2007 in PubMed, PsycINFO and PsycARTICLES, resulting in 45 studies. Within these findings, they discovered that the most common instrument used to measure depression was Center for Epidemiologic Studies-Depression (CES-D), which is a measure of depression in the general population (Radloff, 1977). Thirty-seven of the 45 studies results supported an association between neighborhood characteristics and depression. This association was found after controlling for age, race, ethnicity, gender, marital status, education,
and income. Twenty-four of the 45 studies found an association between structural neighborhood characteristics and depression though it was discovered that structural neighborhood characteristics were less consistent than functional neighborhood characteristics, 52% to 68% respectively. Also, controlling for individual level factors reduced the extent of association with neighborhood characteristics but did not eliminate it.

Structural neighborhood characteristics associated with depression were residential stability, walkability, neighborhood poverty, economic disadvantage index (such as the GINI index), neighborhood cohesion, poor quality housing, low neighborhood SES, availability of automobile transport, material deprivation, neighborhood disadvantage, household income, crime rate per neighborhood, and built environment (Mair et al, 2008). Muntaner, Eaton, Miech, & O’Campo (2004) found marginal standards of living which included renting versus owning and no access to a vehicle (e.g., a car or van) for transportation associated with depression.

**Maternal depression.** When examining maternal depression, there are limited studies (Eastwood et al., 2013b). Nevertheless, maternal depression (defined by the Composite International Diagnostic Interview, short form) has been found to be associated with neighborhood poverty using U.S. census tracts (Delany-Brumsey, Mays and Cochran, 2014). In the United Kingdom, maternal depression was associated with low employment, high ethnic minorities, and limited home ownership at the neighborhood level using the Malaise Inventory (Barnes et al., 2011). Others have discovered mixed results with structural neighborhood characteristics (Barnes et al., 2011; Mair, et al, 2008; Wainwright, 2004).

**Postnatal depression.** When focusing on PND, six studies have examined the neighborhood characteristics and none of these are within the United States. The first, Tannous et
al. (2008) conducted a population-based cross-sectional study in Southern Brazil. They used the EDPS to operationalize depression, specifically, a score of 13 or higher. Through their study, an association was found between per capita income and PND after controlling for confounding factors.

The most extensive examination of PND and neighborhood characteristics was conducted in South West Sydney, Australia. The researchers conducted a concurrent mixed methods study with a main rationale of triangulation (Eastwood et al., 2014c). The methods used in this study were interviews, focus groups, exploratory factors analysis, regression, and multilevel Bayesian spatial data analysis, and integration of quan and qual findings. A main aim of this study was to build a social epidemiology theory of maternal depression using a critical realist “Explanatory Theory Building Method” (p.1). Also from the study, a further explanation of the social determinants of maternal depression, specifically PND, was expected (Eastwood, et al. 2014c).

Eastwood (2011) identified group level variables from his qual arm that consisted of focus groups of mothers and interviews of maternal health professionals, through his dissertation and subsequent studies. These themes were social networks, social capital/cohesion, disadvantaged communities, health behaviors, access to services, big business, social policy, ethnic segregation or integration, global economy, and media (Eastwood et al., 2013b; Eastwood et al., 2014a, 2014b). From these themes, the investigators identified empirical variables by utilizing 2001 Australian census data, Australian crime data, and aggregated individual-level variables from Ingleburn Baby Information System (IBIS) database. An exploratory factor analysis (EFA) was conducted on these 26 variables resulting in six factors: disadvantaged communities, social cohesion, health behaviors, housing quality, access to services, and social
capital (Eastwood et al., 2014a, 2014d). Following the EFA, Eastwood et al. (2014d) applied a Bayesian spatial linear regression with two outcome variables: EPDS > 9 and EPDS > 12. The results for EPDS > 9 were no support, Entropy Index (a measure of diversity), percent living in apartments, and percent smoking. For EPDS > 12, no support, Entropy Index, and no regret leaving suburb were found to be statistically significant.

**Theoretical Conceptualization of PND**

Historically, biological and psychological approaches have been used to address PND etiology. The biopsychosocial approach is an integrated approach that has recently been applied to postnatal depression (Westall & Liampittong, 2011). Contemporarily more advanced approaches are being used to conceptualize health outcomes because current thought is that PND is resulting from a multifactorial contextual framework. These are theory-based frameworks that focus upstream and are ecological (DiClemente, Crosby, & Kegler, 2009). This section will deliver a summary of the biological, psychological, biopsychosocial and the social determinants of health approach to conceptualizing PND.

**Biological Model**

The medical model, a biologically based model, is the dominant model for PND classification and treatment (Westall & Liampittong, 2011). From a biological perspective, Zonana and Gorman (2005) conducted a study of the neurobiology of postpartum depression. One of the first caveats provided by the investigators was that causality was not established for PND. What they did discover from their literature review was that hormonal changes are associated with PND. Specifically, estradiol and testosterone spike before birth and then subside a few days after birth. Estradiol, testosterone, along with progesterone, modulates
neurotransmitters such as serotonin and dopamine (O’Hara & McCabe, 2013). It is suggested that some women may be sensitive to these hormonal changes. Others have supported this association with hormonal balances. Buckwalter et al. (1999) conducted a repeated-measures study of pregnant women. By taking blood samples 2 months before delivery and 2 months after birth. They found that higher levels of progesterone were associated with mood disturbances during pregnancy. After pregnancy, higher levels of testosterone were associated with mood disturbances. Others argue that all women experience these hormonal shifts before and after giving birth and currently there is little evidence supporting differences in hormonal levels between depressed and non-depressed women (O’Hara & McCabe, 2013).

Another biological approach is from evolutionary biology. Hahn, Holbrook, and Haselton (2014) draw upon an evolutionary-mismatch framework. The investigators posit a mismatch of modern society when compared to ancestral practices based on differing resources. They suggest in modern society there is a mismatch in diet, breast-feeding, exercise, sun-exposure, and childcare strategies. For example, the hunter-gatherer diet was richer in “micronutrients, fiber, and fatty acids” (p. 396) when compared to modern society. For breast-feeding, based on prehistoric fossils, it is estimated that prehistoric infants were breast-fed primarily for about 1.5 years and weaned between 2 and 4 years of age. It is suggested that breast-feeding may have protective effects against PND. The other mismatches share a common theme with current rates differing between ancestral and modern humans, which place the modern woman at a risk – less exercise, less sun exposure, and less social support from caregivers.

Finally, Hagen (1999) suggested a mother’s negative affect is hypothesized to result in the less than optimal environmental conditions, e.g., inadequate social support. This negative
affect has been named “psychological pain” (p. 3). From this psychological pain, the mother is able to negotiate for increased resources such as optimal social support. The psychological pain theory supports minor depression during the postpartum period but it does not support other correlates such as fatigue, weight loss, suicidal ideation, and loss of interest in normal activities (Hagen, 1999). To counter this, Hagen (2002) offered that PND is a bargaining strategy to maintain biological fitness or optimal reproductive fitness. From this perspective, the mother could use the associated signs and symptoms of PND to bargain with partner and others. From the study, Hagan (2002) found PND levels were associated with increased investment by partner, i.e., the mother who experienced PND elicited increased social support from the father.

**Psychological Model**

A cognitive-behavioral model has been proposed providing etiology of PND. Specifically, O’Hara, Rehm, and Campbell (1982) suggested that psychological vulnerabilities exist for the individual mother that is elicited during a high stress event such as giving birth. In addition, a stress-vulnerability model has been applied within the cognitive-behavioral model. With this adjunct to the stress-vulnerability model, the mother’s historical data was integrated into the conceptualization such as previous depression and other dysfunctional cognitive process (O’Hara & McCabe, 2013). Additionally, Beck (2002) solicited an interpersonal model for explaining the etiology of PND. This model focused on the mismatch between the mother’s desired social support versus the actual social support she received. Overall, few psychological theories have been proposed since these initial models (O’Hara & McCabe, 2013).
Biopsychosocial Model

Westall and Liamputtong (2011) argue for a biopsychosocial model to gain a robust understanding of PND. They suggest that a biomedical or other singular theory does not encompass the dimensions that influence PND. The biopsychosocial model, as the name suggests, has three dimensions – biological, psychological, and social. The biological component can be understood as a physical expression of depression, such as lethargy. The psychological is understood as the cognitive processes that bring about awareness of a depressive state. The social is the interaction of the individual with the social environment such as withdrawal from social interaction. Additionally, this model posits that illness is an interaction across components that arise from a variety of levels – individual to the society (Borrell-Carrio, Suchman, & Epstein, 2004).

Ross, Sellers, Gilbert, Evans, & Romach (2004) conducted structural equation modeling of PND using the biopsychosocial model. They modeled four types of factors - biological, psychosocial, anxiety, and depression. The biological factors included plasma progesterone and plasma cortisol concentrations. The psychosocial were education, relationship status, income, and unplanned pregnancy. The anxiety factors were based on the participant’s response to specific items within the Brief Symptoms Inventory (BSI). The depression factor was derived from the BSI as well. From the structural equation modeling, the authors determined that the biological factors did not have a direct effect on PND but were mediated by the psychosocial factors and anxiety factors. They concluded that PND is a multifaceted, complex phenomenon and that it is essential to collect data on the psychosocial factors even when the main outcome variables are biological.
Social Determinants of Health Model

The World Health Organization (WHO) and other science fields recognize that health is a complex phenomenon (WHO, 2010; Roy & Campbell, 2013). WHO stated the following in a 2010 report, “Complexity defines health . . . now, more than ever, in the age of globalization” (WHO, p. 4). From this perspective, this study utilized the social determinants of health conceptual framework offered by the Commission on Social Determinants of Health (CSDH).

CSDH social determinants of health. The CSDH framework is founded on the idea that health is a social phenomenon. Within this social experience, the central phenomenon is a person’s social position. This social positioning is configured from political, social, and economic structural mechanisms. Moreover, gender, race, ethnicity, education, income, and occupation stratify this social positioning. The social positioning of the individual shapes their health status establishing a health differential or inequality across a continuum (WHO, 2010). In short, this framework aims to reduce health inequality that is defined as “the unfair and avoidable differences in health status” (Braveman, 2006).

The context and structural elements. Within the CSDH framework, context has a broad definition and cannot be directly measured at the individual level. The context maintains the hierarchical structure, social stratification, through structural mechanisms in the particular society. The mechanisms for maintenance are the social and political characteristics such as “the labour market; the educational system; political institutions and other cultural and societal values” (WHO, p. 5). These structural devices interact constructing an individual’s social positioning.
Intermediary elements. Intermediary determinants are operationalized through “material . . . psychosocial . . . behavioral . . . biological [factors] and the health system” (WHO, p. 6). The material circumstances can be defined through housing, neighborhood, financial, and workplace characteristics. Psychosocial factors are the social support, stress from environment (family, neighborhood, etc.), and coping competencies. The behavioral factors are captured through genetics, epigenetics, nutrition, physical activity, and tobacco/alcohol consumption. The healthcare system has its own effect on the client, such as access to services. Finally, social cohesion and social capital are not restricted but cut across structural determinants and intermediary determinants (WHO, 2010).

SDH, mental health, and PND. Few studies have examined the link between social determinants of health and mental health (Liang et al., 2012). Nevertheless, mental illness must be understood as stemming from multiple determinants – biological, social, economic, and cultural (Ross, Sellers, Gilbert, Evans, & Romach, 2004; Liang et al., 2012; Westall & Liamputtong, 2011). Additionally, mental health can be conceptualized as having multiple levels of influence, from micro to the macro (Conyne & Cook, 2004).

In this effort, Liang, et al. (2012) conducted a study examining depression (defined thorough the Beck Depression Inventory-II) using the SDH framework. They conducted a cross-sectional study of rural Chinese residents who were 18 years and older. They utilized three SDH variables – negative life events, social cohesion, and socioeconomic status. They controlled for demographic variables such as age, gender, and marital status. From a logistic regression analysis, the authors discovered that depression was associated with negative life events, social
cohesion, and socioeconomic status while controlling for confounders. While not strictly defined by PND, it does provide initial evidence for the value of the SDH framework with depression.

**Treatment Strategies for PND**

There have been four main counseling approaches found to be effective for the treatment of PND. They are brief psychodynamic therapy, cognitive behavioral therapy, psychodynamic therapy, and interpersonal psychotherapy (O’Hara & McCabe, 2013). Based on two meta-analyses, the effect size for psychological treatments were medium when compared to controls, Cohen’s $d = 0.51$, 95% CI [0.34, 0.689], $p < 0.001$ and Hedges’ $g = 0.57$, 95% CI [0.38, 0.75], $p < 0.001$ (Cuijpers, van Stratten, Bohlmeijer, Hollon, & Andersson, 2010; Sockol, Epperson, & Barber, 2011). Also within the therapeutic framework, women who are experiencing mild to moderate symptoms of depression, as indicated by the EPDS, brief individual counseling and interpersonal therapies have been found to be efficacious (Austin, 2003). The efficacy of psychopharmacology is still under investigation. O’Hara and McCabe (2013) conducted a literature search of current effective psychopharmacological treatments for PND. They discovered only one study was sound and indicated “clear evidence” (p. 395) over placebo. They noted that most studies had high attrition rates resulting in small samples sizes leading to inadequate power. Yet some have suggested this is the most common modality (Pearlstein et al., 2006).

Besides the counseling treatment approaches, Hahn et al., (2014), based on the mismatch hypothesis, suggested that women increase their intake of vitamin D and omega-3 fatty acids. This approach also advocates for increased exercise, sun-exposure, and fish consumption. The authors also support increasing the breastfeeding rates.
Prevention Strategies for PND

From a prevention perspective, the verdict is still out. The majority of the studies conducted have found mixed results. For example, Dennis (2005) conducted a meta-analysis examining all “published and unpublished randomized controlled trials” (p. 1) aimed to prevent PND. Dennis uncovered 15 trials with 7,697 women involved. Overall, the meta-analysis did not discover a statistically significant association (relative risk 0.81, 95% CI [0.65, 1.02]. Yet, the author did advocate for the potential to reduce the prevalence of PND thorough interventions due to the significant heterogeneity between the trials ($I^2 = 68.8\%$) with results suggesting a 19% reduction in PND.

Home Visitation

Though overall findings on prevention strategies are mixed, a specific prevention strategy that has been found effective for PND is home visitation (Ammerman et al., 2013; Leis, Mendelson, Tandon, & Perry, 2009). Home visitation programs, initially aimed to prevent child abuse and neglect (Ammerman et al., 2007), have currently expanded their scope of practice to include “parenting skills, the mother-child relationships, home safety, maternal health, and infant nutrition” (Ammerman et al., 2005, pp. 1-2). Through home visitation program home visitors, typically a nurse, social worker, or paraprofessional, will work with families and their young children providing case management, and psychoeducation (Ammerman et al., 2009). A child may enter into a home visitation program prenatally and stay in the program until 5 years of age (Ammerman et al., 2005). What is to be noted is that conventional home visitation alone has minimal impact on maternal depression (Ammerman et al., 2009). What has been discovered is
the further expansion of home visitation programs to include mental health treatment to increase the efficacy of this intervention.

Leis et al., (2009) assessed randomized controlled trials (RCT) of home-based counseling interventions for the prevention and treatment of PND. They searched PubMed, PsycINFO, Embase, and CINAHL from commencement to February 2008. The inclusion criteria were a focus on prevention or treatment, study sample of women with a child less than 1 year old, and published in an English language peer-reviewed journal. Through the literature search, they discovered six studies and found four of the six studies with statistically significant results. Non-directive counseling, CBT interventions, and psychodynamic therapies were found to be effective in reducing PND. One study examined non-directive counseling to prevent PND and no statistically significant effect was discovered. The authors recommended future research to (1) concentrate on empirically-based prevention interventions since only one study was found, (2) provide a theory of change, (3) examine moderators and mediators in study design, (4) use standardized methods for reporting findings such as The Consolidated Standards of Reporting Trials (CONSORT), and finally, (5) focus attention on high risk groups such as low-income minorities.

Summary

Postnatal depression, or PND, affects an estimated 13% of women in the United States (Leigh & Milgrom, 2008). If not treated PND may not self-limit, expanding to postnatal psychosis and/or recurrent depressive episodes. Numerous studies have identified the individual level risk factors such as low self-esteem, history of maternal depression, history of anxiety, and many others as well as the effect of PND on maternal offspring (O’Hara & McCabe, 2013). Yet
few studies have examined contributing effects of structural neighborhood characteristics on PND, though some studies outside of the United States have discovered that per capita income, percent no support, Entropy Index, percent living in apartments, and percent smoking are associated with risk of PND (Tannous et al., 2008; Eastwood et al., 2014d). This study helps to fill the gap by examining structural neighborhood effects on PND potential in women participating in a home visitation program in Hamilton County, Ohio.
CHAPTER 3 - Methods

A retrospective cohort design was implemented to study women at risk for PND in Cincinnati, Ohio, who are enrolled in a home-visitation program. This chapter is arranged first by offering the research design and rationale. After this, the study’s setting is described and then the data sources are explained. Based on the data sources, the study variables are presented and operationalized. Finally, the data analysis plan is delivered.

Research Design and Rationale

This study applied a retrospective cohort design (DeForge, 2010). Through a spatial join at the individual level, the outcome variable and control variables were linked with the neighborhood level, 2010 U.S. census tracts, predictor variables creating clustered or lattice data structure. This led to within-cluster error correlation. When this type of correlation is not controlled, “very misleadingly small standard errors and consequent misleadingly narrow confidence intervals, large t-statistics, and low p-values” (Cameron & Miller, 2013, p. 4) can become evident. One way to control for this clustering is to use a HLM modeling approach. Yet this type of modeling requires additional assumptions and is not as parsimonious as other approaches. A simpler modeling approach that can account for this nuisance clustering is a design-based method, DBM, (McNeish & Stapleton, revision invited). This method can use a generalized estimating equation (GEE) model and robust standard errors (Cameron & Miller, 2015; McNeish & Stapleton, revision invited). Through the DBM, the standard errors are estimated “without bias, yielding Type I error rates at the nominal level” (McNeish, 2014, p. 552).
The specific DBM used for this study was a marginal model, GEE, using a quasi-likelihood method with robust standard errors (Argesti, 2013). The rationale for this approach was that the data are naturally clustered – not derived from a complex sampling approach (McNeish & Stapleton, revision invited) and the sample was cross-sectional, i.e., individuals are within U.S. census tracts (Cameron & Miller, 2015). Another reason for this approach was that regression coefficients were of interest based on the research questions. If the variance components were of interest, then an HLM approach would be more appropriate (McNeish, 2014). Additionally, model-based approaches such as HLM with sparsely clustered data and specifically counts of 5 or below per unit at Level 1 may bias estimates and overestimate the variance components (Theall et al., 2011). McNeish (2011), through simulation, has discovered that DBM with GEE outperforms HLM modeling with sparse data and “provided unbiased estimates of the regression coefficient estimates and their standard errors. In fact, “DBMs are negligibly affected by sparse clusters . . . provided the clusters are large . . . for the 2014 paper [I] found no problem with average cluster sizes as small as 1.5 (with about half of the clusters only having 1 observation” (McNeish, D, personal communication, July 17, 2015). For this study, the cluster number was large: 135 clusters with an average cluster size of 5 participants.

Setting

Every Child Succeeds (ECS) is a community-based home visitation program in Hamilton County, Ohio and Northern Kentucky Counties. The program’s efforts are aimed at first-time mothers and their infants with a goal to “ensure an optimal start, both physically and emotionally, for children (ECS, n.d.). To be eligible for the program, a mother must meet one or more of these criteria: unmarried, inadequate income, less than 18 years of age, or
poor/inconsistent prenatal care. The mothers can be admitted to the program during pregnancy or before her offspring reaches three months of age (R. Ammerman, personal communication, August 12, 2013). The ECS program uses two United States based models which are Healthy Families America and Nurse-Family Partnership (Ammerman et al., 2007).

Based on the 2014 ECS Report Card (ECS, 2014), the women who enrolled in the ECS program were unmarried (91%), low income (96%), younger than 18 years of age (24%), and received inadequate prenatal care (30%). When examining race and ethnicity, White (55%), African American (37%), and Hispanic (5%) was reported by women enrolled in the program. Additionally in a 2012 report, mothers enrolled reported significant challenges in areas such as substance abuse, social isolation, and mental illness (ECS, 2012).

ECS completes a variety of screening questionnaires with their enrolled population. In this study, the EPDS and interpersonal support evaluation list (ISEL) were used. ECS also collects demographic and social information on all enrolled mothers, including race, ethnicity, marital status, living arrangements, and educational level (R. Ammerman, personal communication, August 12, 2013).

Data Sources/Sample

Every Child Succeeds

The sample was retrieved from a secondary database, eECS. The target sample was all women enrolled in Every Child Succeeds, from 2006 to 2011, who received a three-month EPDS score $\geq 10$. The three-month EPDS target was chosen based on the limitation with the ECS database and ECS program infrastructure. Three months after initial enrollment in ECS,
women are required to complete the EPDS. Before the third month, some women will take the EPDS, but it is not mandatory (R. Ammerman, personal communication, August 12, 2013).

To identify mothers at risk of developing PND, researchers need to identify a cut score on a screening instrument that provides reasonable sensitivity and specificity. An early cutoff used for this purpose was an EPDS score of 12.5 or greater (Cox et al., 1987) and most studies have used a 9/10 or a 12/13 cutoff (Hanusa, Scholle, Haskett, Spadaro, & Wisner, 2008). The cutoff of 9/10 has been characterized as ‘possible depression’ and 12/13 as ‘probable depression (Cox et al., 1987). Hanusa et al. (2008) conducted a study examining different screening instruments for postpartum depression in a home visitation program for low-income women ($n = 123$). They compared the EPDS, Patient Health Questionnaire (PHQ-9), and Postpartum Depression Screening Scale (PDSS). Their results suggested that an EPDS cutoff score of $\geq 10$ yielded the best sensitivity and specificity in a low-income home visitation program. The EPDS was determined to be a more accurate screening tool for women enrolled in a home visitation program when compared to the PHQ-9 and PDSS screening tools (Hanusa et al., 2008). Ninety-six percent of the women enrolled in the ECS home visitation program, as noted above, reported to be low-income. Based on this demographic and the Hanusa et al. (2008) recommendation, the EPDS score cutoff of $\geq 10$ was utilized within this study to identify women at risk of developing PND.

There are six well-known home visitation programs (Azzi-Lessing, 2011). The ECS program utilizes two of the six, as noted above. Each national and international program has its own programmatic goals but some goals in common such as targeting optimal development early in a child’s life (Azzi-Lessing, 2011). The ECS program may not align with the programmatic
goals with other home visitation programs. This ECS sample is predominately urban, low-income, and within the United States. This may not be true of all home visitation programs, i.e., some home visitation programs may operate in rural communities and internationally (Concha-Eastman, 2016). Also, the entry criteria to the program may be different than that of other home visitation programs. Finally, the 3-month collection point may produce selection bias in that it may not capture women at risk who dropped out of the program before that time-point. Based on the selected sample and points noted, the sample may not represent other home visitation programs. This may impact the generalizability of results found within this study.

**Dependent Variable**

The dependent variable was EPDS total score that ranged from 10 to 30. The EPDS is a postnatal depression scale instrument that ranges from 0 to 30 and the most widely used screening instrument for PND. It is a self-administering instrument consisting of 10-items on a 4-point scale. The screening criteria are based on the client self-report within the past seven days. EPDS has high internal consistency, $r = 0.88$ and high convergent validity with BDI-II, $r = 0.82$. The EPDS has sensitivity that ranged from 55% to 81%, specificity of 88% to 99%, positive predictive power of 56% to 93%, and negative predictive power, 94% to 99% (King, 2012).

**Control Variables**

From the current literature review, the social determinants of health theory, and the examination of individual level variables in the eECS database, the following variables have been identified as the control variables in the model: maternal education, maternal ethnicity, maternal income, maternal age, maternal marital status, maternal race, and maternal social support. These variables were used to remove or subtract their effect so a more accurate
understanding of the predicator variables influence on the outcome of PND is evident (Vogt, 2007).

**Maternal education.** From the ECS screening form, education (in years) was defined by the following categories – “none,” “GED,” “high school diploma,” “associate’s degree,” “bachelor’s degree,” and “master’s degree.” The variable was recoded into “less than high school” = 0, “high school graduate” = 1 “some college” = 2, and “college graduate” = 3.

**Maternal ethnicity.** From the ECS screening form, ethnicity was categorized as “Hispanic/Latina/o.” Hispanic/Latina/o was “no” or “yes” and was coded 0, 1.

**Maternal income.** From the ECS screening form, income was retrieved from the “hourlywage” field. The “hourlywage” is in dollars and cents, e.g., “6.10.”

**Maternal age.** During the mother’s intake the mother’s date of birth (DOB) was recorded. For this study, mother’s age was calculated by subtracting mother’s DOB from “today’s date.” The new variable was “mother’s age” in ## format.

**Maternal marital status.** Through the ECS screening form, marital status was defined as “single,” “never married,” “married,” “separated,” “divorced,” “widowed,” or “unknown.” It was recoded “married” = 0, “divorced” = 1, “separate” = 2, “widowed” = 3, and “single, never married” = 4.

**Maternal race.** Race was extracted from the eECS database. The ECS program collected this information via a demographic questionnaire. In the questionnaire, race was defined as – “White,” “Black or African American,” “Native Hawaiian or other Pacific Islander,” “Bi-racial,” Asian,” “American Indian or Alaskan Native” or “Other.” Due to the small counts (n = 17) of
races outside of “White” and “Black or African American”, race was recoded into “White” = 0, “Black or African American” = 1, and all others combined equal to 3.

**Maternal social support.** The ECS program collected perceived social support from the Interpersonal Support Evaluation List (ISEL). This 40-item scale has four subscales – tangible support, belonging support, self-esteem support, and appraisal support. A higher score indicated increased perception of social support. The items are on a four-point scale from “Definitely True” to “Definitely False” (Cohen & Hoberman, 1983). For this study, the client’s total ISEL score was used in the model.

**United States 2010 American Community Survey**

**Contextual variables.** Based on a literature review, theory, and the review of the 2010 American Community Survey five-year U.S. census tract level data, the following predictor variables have been identified for the study: GINI index of income inequality, percent renting, per capita income in the past 12 months, percent unemployed, percent native of U.S., residence same in past year, and percent renting.

U.S. census tracts are geographic units that are defined by the United States Census Bureau. For this study, the 2010 Tiger/line definitions for census tracts were used. A census tract is a subdivision of a county with a population ranging from 1,200 to 8,000 (see Appendix A). The census tract size is contingent on density, i.e., the denser, the smaller the census tract (United States Census Bureau, n.d.).

Census tracts are the most common definition for neighborhoods. The United States Census Bureau designed tracts with the intent that all individuals within a census tract have a uniform experience and the boundaries between tracts are significant and trustworthy. Finally,
smaller geographic boundaries (census block group) or larger geographic boundaries (place or county) are not different from census tract (Kramer, Cooper, Drews-botsch, Waller, L. A., & Hogue, 2010), i.e., the operational unit used to define neighborhoods does not seem to matter, in that many of the risk factors or effects are found at various levels, such as block groups, tract, and counties (Sampson, 2002). Yet, other studies have found census tract and census block group to be superior; the best detection was found at these boundary levels (Krieger, N., Waterman, P., Chen, J., Soobader, M., & Subramanian, S., 2003a, 2003b, 2003c).

The census tract data was extracted from NHGIS (National Historical Geographic Information System) developed by the Minnesota Population Center of the University of Minnesota unless noted otherwise below. It can be found at [https://www.nhgis.org](https://www.nhgis.org). The NHGIS provides free online access to United States Census data as well as geographic data, e.g. state, county, and census tract boundaries. Specifically, the five-year estimates, 2006-2010 American Community Survey dataset was used. The rationale was that U.S. Census Bureau changed the survey questionnaire from a long form to a short form in 2010. The long form is now captured in the American Community Survey, i.e., to gain access to housing, poverty, and demographic data it is the only source. Additionally, five-year estimates were used over the one and three-year estimates because they are more reliable and are the only estimates that are at the census tract level (Minnesota Population Center, 2011).

**GINI index of income inequality (B19083).** The United States Census Bureau defined the GINI index of income inequality as “ranges from zero (perfect equality) to one (perfect inequality), [and] . . . presented for household income” (U.S. Census Bureau, n.d., p. 127).
**Per capita income in the past 12 months (B19301).** The per capita income was calculated by taking all sources of income of residence within a geographical unit, census tract, and dividing by the total population (United States Census Bureau, n.d.).

**Percent no vehicles available (B25044).** This variable was created by combining “no vehicle available, owner occupied” and “no vehicle, renter occupied” and then dividing by the total count for the census variable and times 100 for a percent (Minnesota Populations Center, 2011).

**Percent residence 1 year ago in the same house (B07013).** This variable was derived from two census variables. The first was the count per census tract of residence that reported staying in the “same house 1 year ago.” The second variable was the “total” count of residence per census tract. The variable was derived by dividing the count of residence who reported staying in the same house in the past year divided by the total count per census tract times 100 (Minnesota Populations Center, 2011).

**Percent renting (B25003).** This variable was derived from two census variables. The first was a count of renters and the next the total count per census tract. The derived variable had the count of renters as the numerator divided by the total count times 100 (Minnesota Population Center, 2011).

**Percent minority (B02001).** This variable was derived by dividing all minority status groups (Black, American Indian, Asian, Native Hawaiian, other race, and combined race) by the total count times 100.
**Percent unemployed (B23001).** Percent unemployed was created by dividing all those within the census that stated they were “not in labor force” and dividing by the total count times 100.

**Percent U.S. citizen (B05012).** This variable was established by dividing those in the census that identified as “Native” and dividing by the total count times 100.

**Percent food stamps or SNAP (B22005B).** This is the “receipt of foods stamps in the past 12 months by race of householder.” The variable was divided by the count of those reporting food stamps or SNAP benefits, divided by the total count times 100 (United States Census Bureau, p. 63).

**Percent in poverty (B17001).** The United Census Bureau (n.d.) defined poverty as:

Since poverty is defined at the family level and not the household level, the poverty status of the household is determined by the poverty status of the householder. Households are classified as poor when the total income of the householder's family in the last 12 months is below the appropriate poverty threshold. (For nonfamily householders, their own income is compared with the appropriate threshold.) The income of people living in the household who are unrelated to the householder is not considered when determining the poverty status of a household, nor does their presence affect the family size in determining the appropriate threshold. The poverty thresholds vary depending upon three criteria: size of family, number of children, and, for one- and two-person families, age of the householder (p. 102).

No recoding was conducted on this variable.
Data Analysis

Description of the Data

The analyses were conducted in SAS® Studio 3.4 and R® 0.98.978. A raw data check was the first step in the data analysis. The raw data check for the continuous variables, dependent and independent, included the n, mean, and standard deviation (Table 1). The raw data check for categorical variables, control variables only, consisted of n and percent (Table 2). The final count for the census tract was 127.
Table 1

Descriptive Statistics of Continuous Variables

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<th>Variable Name</th>
<th>$N$</th>
<th>$M$</th>
<th>$SD$</th>
</tr>
</thead>
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<tr>
<td>EPDS Score</td>
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<td>14.02</td>
<td>3.77</td>
</tr>
<tr>
<td>Mother’s Hourly Wage</td>
<td>313</td>
<td>4.10</td>
<td>4.47</td>
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<tr>
<td>Mother’s ISEL Score</td>
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<td>33.68</td>
<td>14.73</td>
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<tr>
<td>Mother’s Age</td>
<td>313</td>
<td>27.74</td>
<td>5.02</td>
</tr>
<tr>
<td>Gini Index</td>
<td>313</td>
<td>0.45</td>
<td>0.07</td>
</tr>
<tr>
<td>Per Capita Income</td>
<td>313</td>
<td>3171.73</td>
<td>1860.63</td>
</tr>
<tr>
<td>% No Vehicle Available</td>
<td>313</td>
<td>22.87</td>
<td>18.90</td>
</tr>
<tr>
<td>% Same Residence, 1 year ago</td>
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<td>78.14</td>
<td>10.09</td>
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<tr>
<td>% Renting</td>
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<td>55.60</td>
<td>25.72</td>
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<td>% Unemployed</td>
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<td>% U.S. Citizen</td>
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<tr>
<td>% Food Stamps or SNAP</td>
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<tr>
<td>% In Poverty</td>
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Table 2

Descriptive Statistics for Categorical Variables

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<th>Variable Name</th>
<th>N</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mother’s Education</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Less than High School</td>
<td>150</td>
<td>50.68</td>
</tr>
<tr>
<td>High School</td>
<td>78</td>
<td>26.35</td>
</tr>
<tr>
<td>Some College</td>
<td>62</td>
<td>20.95</td>
</tr>
<tr>
<td>College Degree</td>
<td>6</td>
<td>2.03</td>
</tr>
<tr>
<td>Marital Status</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Married</td>
<td>26</td>
<td>8.61</td>
</tr>
<tr>
<td>Divorced</td>
<td>4</td>
<td>1.32</td>
</tr>
<tr>
<td>Separated</td>
<td>5</td>
<td>1.66</td>
</tr>
<tr>
<td>Widowed</td>
<td>1</td>
<td>0.33</td>
</tr>
<tr>
<td>Single, Never Married</td>
<td>266</td>
<td>88.08</td>
</tr>
<tr>
<td>Mother’s Ethnicity</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hispanic</td>
<td>16</td>
<td>5.11</td>
</tr>
<tr>
<td>Non-Hispanic</td>
<td>297</td>
<td>94.89</td>
</tr>
<tr>
<td>Mother’s Race</td>
<td></td>
<td></td>
</tr>
<tr>
<td>White</td>
<td>113</td>
<td>36.33</td>
</tr>
<tr>
<td>Black</td>
<td>181</td>
<td>58.20</td>
</tr>
<tr>
<td>Other</td>
<td>17</td>
<td>5.47</td>
</tr>
</tbody>
</table>
**Missing Data**

Missing data can be grouped into three main categories. These are missing completely at random (MCAR), missing at random (MAR), and missing not at random (MNAR). MCAR concludes that the missing data is not correlated with the outcome and unrelated to other variables in the sample. MAR resolves missingness in that an association does exist with the outcome, but the relationship is found with other variables in the model. Finally, missing not at random assumes the missingness and outcome are associated and no other variables can account for this missingness (Enders, 2010; Osbourne, 2008).

The first step was to analyze the sample variables for missing and percent missing. From Table 3, the range for percent missing was from 0.64% to 5% for those variables with missingness. Three control variables evidenced missing data – mother’s education ($n = 16$), mother’s marital status ($n = 11$), and mother’s race ($n = 2$). The next step was to test for MCAR. MCAR was tested using Little’s MCAR test (Little, 1988) in R®. This is a global test for the entire sample to determine if the missing data upholds to the MCAR mechanism. If the data do hold up to the MCAR mechanism then the missingness is ignorable (Enders, 2010; Osbourne, 2008; Tabachnick & Fidell, 2013). The test was not statistically significant, $\chi^2 = 57.89$ (52), $p = 0.27$ using an alpha level of 0.05. Since the missingness meets MCAR and percent missing is low, 5% percent or less (Tabachnick & Fidell, 2013) listwise deletion was applied prior to the analysis in SAS® Studio 3.4.
Table 3
Descriptive Statistics for Study Variables with Missingness

<table>
<thead>
<tr>
<th>Variable Name</th>
<th>N</th>
<th>Missing</th>
<th>% Missing</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mother’s Education</td>
<td>296</td>
<td>17</td>
<td>5.43</td>
</tr>
<tr>
<td>Mother’s Marital Status</td>
<td>302</td>
<td>11</td>
<td>3.51</td>
</tr>
<tr>
<td>Mother’s Race</td>
<td>311</td>
<td>2</td>
<td>0.64</td>
</tr>
</tbody>
</table>

Model Assumptions

Residual plots against the predicated values were implemented to examine linearity and normality (Osborne, 2008). The outcome variable, mother’s 3-month EPDS score, was found to be nonnormal and nonlinear from residual plots and a statistically significant Shapiro-Wilk test, \( W = 0.89, p < 0.0001 \). A Box-Cox analysis was conducted to determine the recommended transformation resulting in a \( \lambda = -1.25 \), suggesting a reciprocal transformation (Ngo, 2012). This transformation was applied and normality was not achieved through the transformation based on residual plots and a statistically significant Shapiro-Wilk test, \( W = 0.94, p < 0.0001 \).

Multicollinearity was examined through the variance inflation factors (\( VIF \)) and the Spearman rank-order correlation coefficient, Table 4 and 5, respectively. Many of the predictors had a \( VIF > 5 \) (Ngo, 2012). Since multicollinearity was discovered, a principal component analysis was conducted to reduce the numerous variables to the components that accounted for the most variance (Tabachnick & Fidell, 2013; SAS, n.d.)
Principal Component Analysis

For a component to be maintained for the GEE model, three rules were applied. The 1st was if an eigenvalue greater than 1 was discovered, then it was obtained for further evaluation. This criterion was founded on the Kaiser’s stopping rule. If a component’s eigenvalue is equal to or less than one, then it does not explain any more of the total variance than a single predicator variable and can be ignored (Tabachnick, & Fidell, 2013; Kaiser, 1960; Vogt, 2007).

The 2nd and 3rd rule were used to further evaluate for viable components. The 2nd rule was about the variable loadings. A component must have at least three variables with loadings > 0.40. The final rule was that a variable, ideally, would have a high loading on one component, > 0.40, and a low loading on another component. All of these rules were used to establish a simple structure (Reynaldo, Lippke, & Pope, n.d.).
Table 4

Variance Inflation Factor (VIF) Analysis of Predictors (n = 313)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Correlations with Outcome</th>
<th>VIF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gini Index</td>
<td>-0.08</td>
<td>5.05</td>
</tr>
<tr>
<td>Per Capita Income</td>
<td>0.09</td>
<td>3.20</td>
</tr>
<tr>
<td>% No Vehicle Available</td>
<td>-0.20</td>
<td>11.75</td>
</tr>
<tr>
<td>% Same Residence, 1 year ago</td>
<td>0.24</td>
<td>2.39</td>
</tr>
<tr>
<td>% Renting</td>
<td>-0.28</td>
<td>10.13</td>
</tr>
<tr>
<td>% Minority</td>
<td>-0.22</td>
<td>3.08</td>
</tr>
<tr>
<td>% Unemployed</td>
<td>-0.08</td>
<td>5.46</td>
</tr>
<tr>
<td>% U.S. Citizen</td>
<td>0.06</td>
<td>1.60</td>
</tr>
<tr>
<td>% Food Stamps or SNAP</td>
<td>-0.15</td>
<td>10.19</td>
</tr>
<tr>
<td>% In Poverty</td>
<td>-0.17</td>
<td>18.31</td>
</tr>
</tbody>
</table>
Table 5

Spearman Rank-Order Correlation Coefficient for Predicators (n = 313)

<table>
<thead>
<tr>
<th>Predicator</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Gini Index</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2. Per Capita Income</td>
<td>0.23</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3. % No Vehicle</td>
<td>0.61</td>
<td>-0.28</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4. % Same Residence, 1 year</td>
<td>-0.36</td>
<td>0.16</td>
<td>-0.60</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5. % Renting</td>
<td>0.49</td>
<td>-0.34</td>
<td>0.89</td>
<td>-0.73</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6. % Minority</td>
<td>0.46</td>
<td>-0.31</td>
<td>0.76</td>
<td>-0.38</td>
<td>0.74</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7. % Unemployed</td>
<td>0.48</td>
<td>-0.31</td>
<td>0.71</td>
<td>-0.38</td>
<td>0.64</td>
<td>0.73</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8. % U.S. Citizen</td>
<td>0.23</td>
<td>0.22</td>
<td>-0.05</td>
<td>0.27</td>
<td>-0.25</td>
<td>0.003</td>
<td>0.05</td>
<td>1.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>9. % Food Stamps or SNAP</td>
<td>0.56</td>
<td>-0.38</td>
<td>0.833</td>
<td>-0.51</td>
<td>0.74</td>
<td>0.74</td>
<td>0.76</td>
<td>0.01</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>10. % in Poverty</td>
<td>0.67</td>
<td>-0.35</td>
<td>0.89</td>
<td>-0.57</td>
<td>0.82</td>
<td>0.73</td>
<td>0.74</td>
<td>-0.04</td>
<td>0.90</td>
<td>1.00</td>
</tr>
</tbody>
</table>

**Geocoding and Spatial Join**

The mother’s addresses were geocoded using ArcGIS 10.1. Through the geocoding process, each mother was assigned a latitude and longitude. This process created a GIS layer file providing a linking variable, the census tract number. A spatial join was then conducted in ArcGIS between the geocoded layer containing individual level data with the census tract level predicator variables. The two table files were joined based on census tract number. Figure 1
illustrates this linking process and sample size. Figure 2 provides a spatial distribution of the participants by census tract and Figure 3 illustrates the spatial distribution of mean EPDS scores by census tract. Both Figure 2 and 3 provide evidence of variation across space.

Figure 1

Final Sample After Geocoding the Mother’s Address and Merging Sample with 2010 Census Tract GIS Layer File
Figure 2
Spatial Distribution of Counts by 2010 Census Tract Where Participant’s EPDS Score was $\geq$ 10

Figure 3
Spatial Distribution of Average EPDS Scores by Census Tract Where Participant’s EPDS Score was $\geq$ 10
Power

Power is understood as the ability to reject a null hypothesis when the null hypothesis is false. A power analysis is required to determine the appropriate sample size needed to have sufficient strength to reject a null hypothesis when it is truly false. To determine power, five components must be known: (1) significance level, (2) sample size, (3) population standard deviation, (4) the difference between the true population mean and hypothesized mean, and (5) directionality of the test (Lomax & Hahs-Vaughn, 2012). Since the data are clustered, a power calculation can be conducted using the intraclass correlation and the design effect. Based on initial calculations from the current sample, the intracluster correlation coefficient (ICC) was 0.015 and the design effect was 1.07. Based on the power calculation offered by Killip, Mahfound, and Pearce (2004), the total sample size necessary is 293.

Designed-Based Modeling (DBM) using Generalized Estimating Equations (GEE)

Aim. A generalized estimating equations (GEE) method, with clustered standard errors, was used to examine the relationship between a at-risk mother’s potential for PND, based on her three-month EPDS score, and her neighborhood characteristics defined by 2010 census tract predictors that were derived into components via a PCA analysis. The GEE method is a semiparametric approach that does not require the assumptions of normality, linearity, or heteroscedasticity (Vonesh, 2012). The GEE method does require the identification of the link function, probability distribution, and a working correlations structure. The outcome variable was positively skewed with a range from 10 to 28 and discrete. Based on distribution of the outcome, ordinal in nature, and after conducting QQ plots the link function used was cumulative logit and the probability distribution was multinominal (Hormish, Edwards, Eiden, & Kenneth,
Though an exchangeable correlation structure is recommended for lattice data, an independent working correlation is required within SAS when using the multinominal distribution to control for the lattice data with sandwich estimators (Agresti, 2013; Hardin, 2003). GEE models are robust to misspecification of the working correlation structure and by using the sandwich estimators the estimates are valid even with misspecification (Agresti, 2013; Hormish, Edwards, Eiden, & Kenneth, 2010). Moreover, the design effect is low, 1.07, and some suggest that the clustering is negligible; a design effect greater than 2.0 is suggestive of significant clustering that needs to be accounted (Delany-Brumsey, Mays, & Cochran, 2014). Yet, it is better to control for the lattice structure with sandwich estimators than ignore it (Agresti, 2013). The control variables will be entered simultaneously into the model. The predictors will be entered manually and the predictors with the lowest QIC, best fit, will be kept in the model (Hardin & Hilbe, 2003).

Model.

\[ \text{CumLogit} \text{EPDS\_Score} = b_0 + b_1(\text{mother’s education}) + b_2(\text{mother’s ethnicity}) + b_3(\text{mother’s income}) + b_4(\text{mother’s age}) + b_5(\text{mother’s marital status}) + b_6(\text{mother’s race}) + b_7(\text{mother’s social support}) + b_8(1^{st} \text{ predictor derived from PCA}) + \ldots + b_nX_n + e \]
Chapter 4 – Results

Introduction

PND is estimated to impact around 13% of women of childbearing age (Leigh & Milgrom, 2008). If left untreated, PND may contribute to later depressive moods resulting in major depressive disorder (Bennet & Sylvester, 2013). As with major depressive disorder, women who are experiencing PND report a loss of appetite, concentration concerns, disrupted sleeping cycles, and depressed mood (The American College of Obstetrics and Gynecology, n.d.). The threat to wellness presented by PND also impacts the mother’s offspring: through the mother’s disrupted caretaking, an infant may experience irritability and developmental delays. If the mother experiences chronic impairment from PND and recurring depressive episodes then a child may develop mental disorders into adolescents such as depression, anxiety, and alcohol abuse (Zajicek-Farber, 2008).

An abundance of research has established individual-level PND risk factors such as history of anxiety, history of depression, maternal poverty, maternal unemployment, birth complications, and others (O’Hara & McCabe, 2013). Yet, currently, limited studies exist examining the maternal neighborhood risk factors (Eastwood, Phung, & Barnett, 2011). Studies have been conducted in Southern Brazil, and South West Sydney, Australia. In Brazil, per capita income was associated with the risk of PND (Tannous et al., 2008). In Australia, neighborhood adversity, social cohesion, health behaviors, housing quality, access to social services, and social networks were identified predictors through a EFA analysis (Eastwood et al., 2013b). Additionally, through a Bayesian spatial linear regression, with the outcome of EPDS > 9, no support, Entropy Index, percent living in an apartment, and percent smoking were associated
with PND. For EPDS > 12, no support, Entropy Index, and no regret leaving suburb were found to be statistically significant with PND (Eastwood et al., 2014d). Because no study was discovered that examined the association of neighborhoods with risk of postnatal depression in the United States, much less with PND potential among at-risk women, this study examined whether maternal structural neighborhood characteristics predicted PND potential in women enrolled in a home visitation program in Cincinnati, Ohio.

**Principal Component Analysis**

As noted previously (see Tables 4 & 5), a number of the predictors were collinear. Therefore, a principal component analysis (PCA) was conducted to reduce the number of variables to those components that account for the majority of the variance (Tabachnick & Fidell, 2013). A varimax orthogonal rotation was used because the components were used as predictors in the GEE model (Tabachnick & Fidell, 2013; SAS, n.d.); an oblique rotation was also conducted with similar results. The Kaiser’s Measure of Sampling Adequacy was conducted with an overall MSA of 0.80 providing sufficient evidence that a PCA was sound for this data set (Tabachnick, & Fidell, 2013). For a component to be maintained the following criteria were used: (1) an eigenvalue greater than 1 must obtained (see Table 6) based on the Kaiser’s stopping rule (Tabachnick, & Fidell, 2013; Kaiser, 1960) because a component that is equal to or less than 1 does not explain any more of the total variance than a single predictor variable and can be ignored (Vogt, 2007); (2) a component must have at least three variables with a loading > 0.40; and (3) a variable ideally has high loading on one component (e.g., > 0.40) and a low loading on another component for a simple structure (Reynaldo, Lippke, & Pope, n.d.). When interpreting the components, predictor variables with a loading equal to or less than 0.32 were
ignored (Bryant & Yarnold, 2010; Tabachnick, & Fidell, 2013). Based on these three standards, two components were kept for the GEE model: Component 1 and Component 3. These two components explained a total of 67.1% of the variance (Table 7) from the set of predictors. Though Component 2 did have an eigenvalue greater than 1.0, it had only two variables with loading greater than 0.40: Gini index (0.79) and per capita income (0.88).

The individual predictor variables that loaded on Component 1 were GINI index, percent no vehicle available, percent renting, percent minority, percent unemployed, percent on food stamps or SNAP, and percent in poverty. By examining these loadings collectively, the underlying theme was unfair access to social resources and opportunities. Socioeconomic stratification is influenced by social context that includes mechanisms such as social class, race, gender, social mobility, political power, occupation, and education (WHO, n.d.). Many of the loadings pointed to neighborhoods with low socioeconomic standings such as poverty, unemployment, and eliciting government assistance such as food stamps (Oakes & Kaufman, 2006). Because the variables for Component 1 illustrated the common theme of low socioeconomic characteristics, this component then was labeled as Social Disadvantage (See Table 8).

Component 3 consisted of percent same residence, one year ago, percent renting, and percent U.S. citizen. It has been suggested that those who rent have increased residential mobility (Hedman & Van Ham, 2012) and that residential mobility is increased when household members experience as sense of disequilibrium (Clark & Huang, 2003). Those who possess U.S. citizenship may have increased tenure and form social ties that contribute to a sense of community. This then may allow for a more stable environment and may limit the
disequilibrium, thereby increasing residential stability (Hedman & Van Ham, 2012). The underlying theme was residential stability. This was labeled as Stability due to the loadings and rationale described above.

Table 6

Principal Component Analysis: Eigenvalues of the Correlation Matrix (n = 313)

<table>
<thead>
<tr>
<th>Components</th>
<th>Eigenvalue</th>
<th>Difference</th>
<th>Proportion</th>
<th>Cumulative</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>5.52</td>
<td>3.89</td>
<td>0.55</td>
<td>0.55</td>
</tr>
<tr>
<td>2</td>
<td>1.63</td>
<td>0.433</td>
<td>0.16</td>
<td>0.72</td>
</tr>
<tr>
<td>3</td>
<td>1.20</td>
<td>0.53</td>
<td>0.12</td>
<td>0.84</td>
</tr>
<tr>
<td>4</td>
<td>0.67</td>
<td>0.29</td>
<td>0.07</td>
<td>0.90</td>
</tr>
<tr>
<td>5</td>
<td>0.38</td>
<td>0.14</td>
<td>0.03</td>
<td>0.94</td>
</tr>
<tr>
<td>6</td>
<td>0.23</td>
<td>0.07</td>
<td>0.02</td>
<td>0.96</td>
</tr>
<tr>
<td>7</td>
<td>0.17</td>
<td>0.07</td>
<td>0.02</td>
<td>0.98</td>
</tr>
<tr>
<td>8</td>
<td>0.10</td>
<td>0.04</td>
<td>0.01</td>
<td>0.99</td>
</tr>
<tr>
<td>9</td>
<td>0.06</td>
<td>0.02</td>
<td>0.01</td>
<td>1.00</td>
</tr>
<tr>
<td>10</td>
<td>0.04</td>
<td>0.00</td>
<td>0.00</td>
<td>1.00</td>
</tr>
</tbody>
</table>
Table 7

Variance Explained by Each Component Maintained for GEE Model After Varimax

(Orthogonal) Rotation (n = 313)

<table>
<thead>
<tr>
<th>Component</th>
<th>Eigenvalue</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Social Disadvantage (PC1)</td>
<td>5.31</td>
<td>53.1</td>
</tr>
<tr>
<td>Stability (PC3)</td>
<td>1.45</td>
<td>14.5</td>
</tr>
</tbody>
</table>
Table 8

Principal Component Analysis: Varimax (Orthogonal) Rotation Factor Pattern for Components

Maintained for GEE Model (n = 313)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Social Disadvantage (PC1)</th>
<th>Stability (PC3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gini Index</td>
<td>0.51*</td>
<td>-0.01</td>
</tr>
<tr>
<td>Per Capita Income</td>
<td>-0.29</td>
<td>0.09</td>
</tr>
<tr>
<td>% No Vehicle Available</td>
<td>0.94</td>
<td>-0.15</td>
</tr>
<tr>
<td>% Same Residence, 1 Year Ago</td>
<td>-0.31</td>
<td>0.78</td>
</tr>
<tr>
<td>% Renting</td>
<td>0.80</td>
<td>-0.51</td>
</tr>
<tr>
<td>% Minority</td>
<td>0.81</td>
<td>-0.11</td>
</tr>
<tr>
<td>% Unemployed</td>
<td>0.91</td>
<td>0.07</td>
</tr>
<tr>
<td>% U.S. Citizen</td>
<td>0.17</td>
<td>0.73</td>
</tr>
<tr>
<td>% Food Stamps or SNAP</td>
<td>0.96</td>
<td>0.01</td>
</tr>
<tr>
<td>% in Poverty</td>
<td>0.95</td>
<td>-0.11</td>
</tr>
</tbody>
</table>

* loading factor > 0.40

Final Sample

The final sample, after listwise deletion, consisted of demographic characteristics of the 295 women outlined in Tables 9 and 10. The mean age was 27 with a range of 19 to 43; most women (57%) reported Black for race. The majority (51%) of the sample had less than a high school degree and 89% recounted being single. The average three-month EPDS score was 14.14.
Table 9

Descriptive Statistics of Continuous Variables After Listwise Deletion

<table>
<thead>
<tr>
<th>Variable Name</th>
<th>N</th>
<th>M</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>EPDS Score</td>
<td>295</td>
<td>14.14</td>
<td>3.81</td>
</tr>
<tr>
<td>Mother’s Hourly Wage</td>
<td>295</td>
<td>4.10</td>
<td>4.47</td>
</tr>
<tr>
<td>Mother’s ISEL Score</td>
<td>295</td>
<td>33.68</td>
<td>14.73</td>
</tr>
<tr>
<td>Mother’s Age</td>
<td>295</td>
<td>27.74</td>
<td>5.02</td>
</tr>
<tr>
<td>Socially Disadvantaged</td>
<td>295</td>
<td>0.02</td>
<td>1.02</td>
</tr>
<tr>
<td>Stability</td>
<td>295</td>
<td>0.01</td>
<td>1.01</td>
</tr>
</tbody>
</table>
Table 10

Descriptive Statistics for Categorical Variables After Listwise Deletion ($n = 295$)

<table>
<thead>
<tr>
<th>Variable Name</th>
<th>$N$</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mother’s Education</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Less than High School</td>
<td>150</td>
<td>50.85</td>
</tr>
<tr>
<td>High School</td>
<td>78</td>
<td>26.44</td>
</tr>
<tr>
<td>Some College</td>
<td>61</td>
<td>20.68</td>
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<tr>
<td>College Degree</td>
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<td>2.03</td>
</tr>
<tr>
<td>Marital Status</td>
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<td></td>
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<tr>
<td>Married</td>
<td>24</td>
<td>8.14</td>
</tr>
<tr>
<td>Divorced</td>
<td>4</td>
<td>1.36</td>
</tr>
<tr>
<td>Separated</td>
<td>5</td>
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<tr>
<td>Widowed</td>
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<tr>
<td>Single, Never Married</td>
<td>261</td>
<td>88.47</td>
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<tr>
<td>Mother’s Ethnicity</td>
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<td></td>
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<tr>
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<td>16</td>
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</tr>
<tr>
<td>Non-Hispanic</td>
<td>279</td>
<td>94.58</td>
</tr>
<tr>
<td>Mother’s Race</td>
<td></td>
<td></td>
</tr>
<tr>
<td>White</td>
<td>109</td>
<td>36.95</td>
</tr>
<tr>
<td>Black</td>
<td>169</td>
<td>57.29</td>
</tr>
<tr>
<td>Other</td>
<td>17</td>
<td>5.76</td>
</tr>
</tbody>
</table>
Association of PND and Maternal Structural Neighborhood Characteristics

Table 11 provides the results from the GEE analysis. The link function was a cumulative logit within the GEE model. The reporting of the results is therefore dependent on this link function. The GEE approach produces measured effects that are at the "population level" (Agresti, 2013). The focus of this study was on maternal structural neighborhood characteristics and if they were associated with the risk of postnatal depression. Based on the GEE analysis, Stability was found to be statistically significantly associated with PND potential, \( b = -0.34, Z = -3.86, p = 0.01 \), when controlling for mother’s education, marital status, ethnicity, race, age, ISEL score, hourly wage, and social disadvantage. Therefore, with a 1-unit increase in Stability there is a log odds decrease (-0.34) in women’s EPDS score. In other words, as neighborhood Stability increases, there is a decrease in the risk of PND potential for those at risk women enrolled in a home visitation program. Social Disadvantage was not found significant, \( p = 0.12 \). Additionally, though not a part of the research question, none of the individual control variables were found to be statistically significant.

A sensitivity analysis was conducted with all three components maintained in the GEE model along with the control variables. From this analysis, Stability continued to be the only statistically significant predictor and the estimates only marginally differed, to the 1/1000, from a model with only Components 1 and 3. Furthermore, the GEE fit criteria, QIC and QICu, increased with all three components in the model; Using only Component 1 and 3, a lower QIC and QICu was evident. This provided the rationale to include only Component 1 and 3 in the final GEE model.
Table 11

Generalized Estimating Equation (GEE) Results with Empirical Standard Error Estimates

<table>
<thead>
<tr>
<th>Variable</th>
<th>Estimate</th>
<th>SE</th>
<th>CI (95%)</th>
<th>Z</th>
<th>Pr &gt;</th>
<th>Z</th>
</tr>
</thead>
<tbody>
<tr>
<td>Social Disadvantage</td>
<td>0.23</td>
<td>0.17</td>
<td>[-0.09, 0.55]</td>
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<td>0.16</td>
<td></td>
</tr>
<tr>
<td>Stability</td>
<td>-0.34</td>
<td>0.10</td>
<td>[-0.53, -0.16]</td>
<td>-3.64</td>
<td>0.01</td>
<td></td>
</tr>
<tr>
<td>Mother’s Education</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Less than High School</td>
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<td>0.77</td>
<td>[-2.16, 0.87]</td>
<td>-0.84</td>
<td>0.40</td>
<td></td>
</tr>
<tr>
<td>High School</td>
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</tr>
<tr>
<td>Some College</td>
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<td>[-1.95, 10.6]</td>
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<td>0.56</td>
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</tr>
<tr>
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<td>0</td>
<td>0</td>
<td>Ref</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Marital Status</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Married</td>
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<td>[-0.63, 0.90]</td>
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<td>0.73</td>
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<tr>
<td>Divorced</td>
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<td>[-2.36, 1.24]</td>
<td>-0.61</td>
<td>0.54</td>
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<tr>
<td>Separated</td>
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<td>0.81</td>
<td>[-1.72, 1.46]</td>
<td>-0.16</td>
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</tr>
<tr>
<td>Widowed</td>
<td>-1.85</td>
<td>1.78</td>
<td>[-5.34, 1.63]</td>
<td>-1.04</td>
<td>0.30</td>
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</tr>
<tr>
<td>Single, Never Married</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>Ref</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mother’s Ethnicity</td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Hispanic</td>
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<td>0</td>
<td>0</td>
<td>Ref</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Non-Hispanic</td>
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<td>0.49</td>
<td>[-0.98, 0.29]</td>
<td>-0.06</td>
<td>0.95</td>
<td></td>
</tr>
<tr>
<td>Mother’s Race</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>White</td>
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<td>-1.01</td>
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<tr>
<td></td>
<td>B</td>
<td>SE</td>
<td>Lower 95% CI</td>
<td>Upper 95% CI</td>
<td>p</td>
<td>OR</td>
</tr>
<tr>
<td>----------------</td>
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<td>-----</td>
<td>--------------</td>
<td>--------------</td>
<td>------</td>
<td>-----</td>
</tr>
<tr>
<td>Black</td>
<td>-0.14</td>
<td>0.47</td>
<td>[-1.06, 0.78]</td>
<td>-0.30</td>
<td>0.76</td>
<td></td>
</tr>
<tr>
<td>Other</td>
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<td>Ref</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mother’s Hourly Wage</td>
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<td>0.03</td>
<td>[-0.03, 0.07]</td>
<td>0.78</td>
<td>0.43</td>
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<tr>
<td>Mother’s ISEL Score</td>
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<td>0.01</td>
<td>[-0.02, 0.01]</td>
<td>-0.15</td>
<td>0.88</td>
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</tr>
<tr>
<td>Mother’s Age</td>
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<td>0.02</td>
<td>[-0.08, 0.01]</td>
<td>-1.54</td>
<td>0.12</td>
<td></td>
</tr>
</tbody>
</table>

**Summary**

Through this study, I investigated the association of PND potential, operationalized as 3-month EPDS scores, with structural neighborhood characteristics among at-risk mothers. From a GEE analysis, Stability was discovered to be statistically significantly associated with PND potential ($p = 0.01$). No other predictors or control variables were found to be statistically significant when controlling for Stability. In the following Discussion section, a further examination of these findings will be deliberated.
Chapter 5 – Discussion

This chapter provides an overview of the study, including the problem statement, research question, research design, and major findings. Moreover, this chapter discusses the findings in relation to extant literature. The later part of this chapter contains the implications for practice, limitations, future research, and conclusion.

Overview of the Study

Postnatal depression takes a toll on about 13% percent of women of childbearing age in the United States. For women who have experienced PND, they reported signs and symptoms of depressed mood, difficulties with sleeping, memory concerns, and loss of appetiteive (Leigh & Milgrom, 2008). Consequentially, women experiencing PND have conveyed decreased adjustment socially and in their marriage (O’Hara et al., 2013). Risk factors identified with PND include a history of anxiety, maternal depression, depression during pregnancy, poverty, and race (O’Hara & McCabe, 2013). A woman may also have recurring depressive episodes over a lifetime if not treated during the postnatal period (Bennett & Sylvester, 2013). Lastly, when a woman experiences PND, it may adversely affect her offspring. Infant, child, and adolescent outcomes associated with PND are premature birth, low birth weight, developmental delays, alcohol dependence, anxiety, and depression (Hubner-Lieermann et al., 2012; Wang et al., 2011; Zajicek-Farber, 2008).

Outside of the individual level risk factors and outcomes identified above, limited studies have examined maternal structural neighborhood characteristics for an association with PND (Eastwood et al., 2014d). This is relevant because increasing evidence points to societal characteristics influencing disease etiology (Blas et al., 2008; Eastwood et al., 2012b). The few
studies that have examined this relationship found per capita income in Southern Brazil and in South West Sydney, Australia factors such as Neighborhood Adversity, Social Cohesion, Health Behaviors, Housing Quality, Social Services, and Support Networks. Moreover, in South West Sydney, through a Bayesian spatial linear regression with an outcome of EPDS > 9 and EPDS > 12, percent of no support, Entropy Index, percent living in apartment, and percent smoking were associated with PND (Tannous et al., 2008; Eastwood et al., 2013b, 2014d)

Via a thorough literature review, no study was discovered that examined the relationship between PND potential and structural neighborhood characteristics in the United States, nor was any study located that examined PND potential among at-risk mothers. To address this gap, the association between PND potential and structural neighborhood characteristic among women enrolled in a home visitation program who were at risk for PND was examined. To accomplish this, a retrospective cohort design was utilized. The cohort consisted of women enrolled in a home-visitation program in Cincinnati, Ohio between 2006 and 2011 who had a 3-month EPDS score ≥ 10. The mother’s residential addresses were geocoded and spatially linked with 2010 Census Bureau American Community Survey census tract data. The census tract variables were the neighborhood level predictors.

Next, a PCA analysis was conducted on the neighborhood level predictors resulting in two components: Social Disadvantage and Stability. These two components represented the neighborhood predictors. To control for the lattice structure a generalized estimating equation (GEE) approach was applied. These predictors along with individual-level control variables were placed in the GEE model. From the GEE analysis, Stability was discovered to be negatively
associated with PND when adjusting for the other predictor and individual-level control variables.

**Findings and Existing Literature**

Neighborhood structural characteristics appear to be associated with the risk of PND, supporting the study hypothesis. Stability, comprised by percent same residence 1 year ago, percent renting, and percent U.S. citizen, may be a protective factor based on the findings of this study. At the time of this study, no other research had been identified that corroborates the finding of Stability as a potential protective factor for PND. Yet, it appears congruent with the social determinants of health theory in that social positioning is a determinant for mental health outcomes such as depression (Liang et al, 2012).

Others have discovered an association with neighborhood stability and health outcomes. Mair et al. (2008) conducted a review of peer-reviewed observational studies of depression and neighborhood characteristics. From this review, they discovered that residential stability was not a consistent predictor of depression. However, one study found a positive association with residential stability and depression; residential stability was defined as living in the same house in past 5 years and was retrieved from the 1990 U.S. Census data (Ross, Reynolds, & Geis, 2000). Ross et al. (2000) revealed that residential stability might be protective for wealthy neighborhoods but have an inverse effect in poor neighborhoods. This finding supports the social isolation theory in that poverty isolates individuals due to not having the resources to escape from deleteriously environments (Ross et al., 2000). Ross et al. (2000) also proposed “social ties among neighbors and social order are among the most important proximate factors . . . [they] mediate the effects of neighborhood stability and poverty on distress” (p. 583).
Boardman (2004) examined residential stability with stress and physical health. He found that stress had a greater influence and a negative impact on physical health in unstable neighborhoods. Boardman (2004) suggested that stable neighborhoods might provide a buffer to stress and the poor health outcomes associated with elevated stress. Specifically, he offered social capital, defined as the gained resources from social neighborhood connections (Sampson et al., 2002), as an important factor associated with neighborhood stability; neighborhoods with increased social capital may have protective qualities insulating against poor health outcomes such as PND. O’Hara et al. (2013) also supported these findings by suggesting that contextual conditions could act as buffers, including social support.

Social Disadvantage, comprised by GINI index, percent no vehicle available, percent renting, percent minority, percent unemployed, percent on food stamps or SNAP, and percent in poverty, was not found to be associated with an increased risk of PND. This finding is different from the expectations of this study. Eastwood et al. (2013b; 2014d) discovered mixed results with Social Disadvantage in their mixed methods study. Initially, Social Disadvantage was identified from the qualitative arm of MMR study but in the preceding quan arm, Social Disadvantage was not found to be statistically significant after controlling for Social Capital and ethnicity (Eastwood, 2013b, 2014d). These mixed findings could be accounted in that the more distal a predictor, the less likely it will be statistically significantly associated with an outcome. For example, Eastwood et al. (2013b) proposed that Social Cohesion and Social Networks, both found to be statistically significant, are less distal to the outcome, PND, than Social Disadvantage. This could provide a rationale why Social Disadvantage was not found to be a significant predictor in their quantitative analysis.
Implications for Practice

Stability and the Client

**Microlevel.** In this study, findings suggested that neighborhood Stability might be a protective factor against the PND potential, defined as an EPDS score greater than or equal to 10, for women who are enrolled in a home visitation program. The core theme of neighborhood Stability, identified by the investigator in this study, is residential stability. Though no literature was identified that corroborated the findings within this study, a practical implication for professional counselors working with home visitation women who are at risk for PND may be examining neighborhood factors such as Stability during the intake. If the client has a high degree of residential mobility, this may impair the client’s ability to attend to the treatment process and be a potential barrier to therapeutic success. This also may impact the attachment between the mother and child (Marcynyszyn, Evans, and Eckenrode, 2008). It may be important for the professional counselor to gain an understanding of the factors that are contributing to the client’s living situation and tailor relevant interventions that may increase a sense of stability (Boardman, 2004; O’Hara et al., 2013).

**Macrolevel.** At the community level, housing policies can be a point of intervention for mothers, who are enrolled in a home visitation program with the potential to experience depression, in that improving housing quality has been associated with increased mental health (Suglia, Duarte, & Sandel, 2011) and frequent residential moves have been linked with depression (Rothwell, German, Latkin, 2008). Also, mental health problems may be precursors to housing instability and housing instability may trigger mental health problems. Finally, mothers who have limited housing options and experiences poor quality housing may have an
increased likelihood for poor mental health (Suglia et al., 2011). It is therefore suggested that increasing the housing quality may be protective for the wellness for these mothers and their child (Suglia et al., 2011). Advocating for affordable housing and increased funding for national, state, and local housing assistance programs are recommended avenues (Cutts et al., 2011). An increase in housing subsidies and safe public housing has evidenced a decrease in evictions that may increase Stability (Phinney, Danziger, Pollack, & Seefeldt, 2007).

**Prevention and Intervention Strategies**

Despite the finding that neighborhood stability was associated with PND potential, it remains largely unknown what neighborhood structural characteristics impact PND. Nonetheless, the limited studies on the topic reveal the importance of prevention across micro and macro levels. The following suggested prevention and intervention strategies are drawn from the current literature on contextual influences on PND and related health concern, depression.

**Stability and Social Capital**

When examining the extant literature on PND and neighborhood effects, no study was discovered that identified Stability as a likely protective factor, but it was located in the depression literature - an association exists between stability, social capital, and depression (Boardman, 2004; Eastwood et al., 2013b; O’Hara et al., 2013; Ross, 2000). Also, social capital has been suggested to be the most proximate effect (Ross, 2000). Therefore, a focus on social capital is presented in this section.

Social capital can be defined as the "amount of investment, resources, and networks in any given locale that in turn produces relationships of trust, mutual aid, cohesion, and engagement” (Blair et al., 2014, p. 884). O’Hara et al. (2013) also suggested “psychological,
social, and environmental risk factors [for postpartum depression] mirror those for depressions outside of the postpartum period” (p. 400). These findings suggest that social capital may be an important consideration for depression and inductively for women in a home visitation program who have an increased risk for PND. Therefore, interventions that have been recommended for depression may also be informative for reducing the risk of PND.

The authors of the social determinants of health framework support the idea that social position influences health outcomes and interventions focused on disrupting health inequality are important (LaVeist, 2005; Wilkinson, 2005). Through the social determinants of health framework interventions are recommended from the microlevel to the macrolevel (Liang, 2011; LaVeist; WHO, n.d.). This then provides the foundation for the practical recommendation offered below.

It is imperative to note that the suggested interventions have not specifically targeted women within a home visitation program who are at risk of PND and Stability, but seem like promising approaches given the books and peer-reviewed articles on social determinates of health and depression. Moreover, our current understanding of societal factors and associated paths (causal paths) to reduce health disparities is in its infancy (Braveman, Egerter, & Williams, 2011; Liang, 2011); therefore, the interventions listed below should be fully vetted and evaluated for their validity. The interventions provided below will move from the microlevel to the macrolevel and are founded on the potential influence of social capital. Social connections can improve, from the individual to the community, in areas such as resiliency, efficacy, sense of control, political power, social networks, trust, and willingness to engage for the greater good (Blair et al., 2014; Braveman et al., 2011; Liang et al., 2011; Wilkinson, 2005).
Microlevel. A potentially viable approach for the counseling profession is to partner with other health and non-health professionals as well as community members (O’Campo et al., 2009); a transdisciplinary approach is recommended (Liang et al., 2011). By establishing and maintaining these relationships, the counseling profession could begin to improve the mother’s stability at the individual, couple, and family level (Jones & Mei, 2015; Wilkinson, 2005). In particular, home-visitation programs can partner with clinical mental health counseling professionals as a referral partner when a mother has been identified as at risk for PND. The counselor can then implement interventions that are tailored to the home-visitation program needs, such as individual, couple, family and/or group therapy, as well as educational groups. The counseling professional can also provide consultation to the home visitation program as an expert in mental health by providing training and other educational opportunities to staff. This is relevant for some home visitation programs that utilize social workers and para-professionals that may not be as qualified to diagnose and treat PND (Ammerman et al., 2013).

Macrolevel. The professional counseling profession may address the social injustices through an advocacy. Health inequality, defined as “systematic differences in health for different groups of people [that] are avoidable” (Marmot, Friel, Bell, Houweling, & Taylor, 2008, p. 1661), contributes to poor health outcomes (Blair et al., 2014; Braveman et al. 2011; Jones & Tang, 2015; Liang et al., 2011; Marmot, 2005; Wilkinson, 2005). This then calls for the individual counselor and the counseling profession collectively to advocate for advancing equality in areas such as education, housing, gender, ethnicity, and race. For example, by advancing gender equality, the counseling profession could possibly increase Stability by bringing about equality in pay, paid maternity leave, and a living wage instead of a minimum
wage. By advancing these areas, a mother may be able to purchase a home instead of renting an apartment, have the financial resources to achieve citizenship, or have the assets to live in a more hospitable environment thereby reducing her risk of PND (Jones & Tang, 2015).

The counseling profession needs to address the incalcitrant inequality in our society. A potential approach to ameliorate inequality is through the socioeconomic and political context of the United States. An approach is collaborating with policymakers at the local, state, and national level to establish interventions, such as policy changes, that will reduce the health gaps between the poorest and richest in the nation. A way to address this is through targeted community-based interventions towards those identified as the most vulnerable. These targeted approaches have an advantage in the ease of implementation and ownership by local community, but they are weak in that it is not a population-based approach and may not address the larger issue of inequality across the country (WHO, n.d.) Therefore, an adjunct to the community-based intervention would be involvement at the higher level by addressing the structural determinants of heath, such as differentials in education and income (Braveman, 2011; Wilkinson, 2005).

The United States has established national health goals through the HealthyPeople 2020 initiative (Office of Disease Prevention and Health Promotion, n.d.). Specific interagency objectives were developed to disarm and possibly eliminate health inequalities. These objectives confront inequality by establishing goals to secure economic stability, access to health care, improve neighborhood environments, and improved social/community interactions (Office of Disease Prevention and Health Promotion, n.d.). These objectives then drive the federal funding and the national, state, and local level government activities to address inequality. The counseling profession can partner with these federal, state, and local entities to establish viable
collaborations designed to reduce and potentially eliminate these inequalities that impact the health of our clients. For example, in Kansas City, Kansas a comprehensive school reform was put into place to address the low graduation rates. This reform equipped the teachers with evidence-based teaching approaches and content. Furthermore, the reform, established teacher advocates to supports’ emotional needs and to assist in the navigating the education system towards increased student success (Office of Disease Prevention and Health Promotion, n.d.). Within this example, school counselors could work with the teacher advocates, as well the local school boards, in designing and implementing such a program. Additionally, professional counseling organization at the national, state, and local level could assist in the evaluation and duplication of this successful program in other areas of the state and the nation.

Limitations

The goal of the dissertation was to examine the relationship between women in a home-visitation program at risk for PND and their neighborhood characteristics. One of the limitations was using 2010 U.S. Census Bureau American Community Survey (ACS) variables to operationalize the structural neighborhood predictors in the study. This confined the structural neighborhood variables available for analysis and limited the comparability to other studies examining PND, such as those conducted in Brazil and Australia. Nevertheless, no other structural database was discovered in Hamilton County that collects the necessary neighborhood level data by census tract. Moreover, the addition of other structural neighborhood factors may not have added additional insight due to the overlapping variance that has been discovered through the analysis of the neighborhood predictors.
Another limitation is the ECS home visitation program and the archival data that was available. First, the ECS program only collects data for women in the program and not population-based. Second, ECS collects a wide range of information on its clients but it is not exhaustive; individual-level risk factors that have been identified in literature such as maternal history of mental illness, birth complications (infertility, anemia, preeclampsia), and birth outcomes (congenital malformation, admission into neonatal intensive care unit (NICU), and Down Syndrome) are not collected. Since not all potential confounders are available, the maternal structural neighborhood effects may be accounted for by other individual level variables (Weich et al., 2003). An additional limitation is based on the entry criteria or eligibility for the ECS program - other home-visitation programs may have differing eligibility criteria that may be a hindrance to the generalizability of the current findings. Finally, the EPDS instrument was used to measure the risk of PND and it is only a screening instrument. A clinical diagnosis would be necessary to provide a diagnosis of depression.

Though these individual-level limitations exist, few programs collect address-level data on PND as ECS. The address level data, along with PND screening data, were necessary for linking the neighborhood structural predictors with individual-level controls. Additionally, even if extra control variables were included, structural neighborhood effects are still relevant for understanding maternal well being (Barnes et al., 2011).

Finally, due to the distribution of the outcome, a marginal model was used, GEE. The GEE approach is an estimation method and not a model since a quasi-likelihood function is used and the empirical estimates may have more variability than parametric estimates (The Pennsylvania State University, 2015). Additionally, the GEE approach generates population-
averaged estimates (Agresti, 2013). This may be a limitation if the research question(s) needed subject-specific or cluster-specific estimates. For this particular study, subject or cluster-specific estimates are not necessary. Finally, using the current analytical approach, I was unable to investigate other effects such as mediation or moderation (e.g., does Stability mediate Social Disadvantage or vice-versa?).

**Future Research**

O’Campo et al. (2009) suggest that multiple pathways contribute to mental health outcomes and that a more complete understanding of these pathways is needed. By discovering these pathways from neighborhoods to mental health outcomes such as PND, this new information may inform programs and interventions that may decrease the risk of PND. A potential way to address this situation is by applying a mixed method research (MMR) framework to extend upon the current study.

A sequential MMR method approach could be utilized longitudinally and would include the gathering of residential surveys, neighborhood observations, and surveys of neighborhood experts across disciplines. Through these collection methods, an investigator could gain an understanding of the functional neighborhood characteristics (group behaviors) because the understanding of functional neighborhood characteristics was found to be a more consistent predictor than structural neighborhood characteristics (Mair et al., 2008; Sampson et al., 2002). Additionally, collecting archival data such as hospital discharge, birth certificate, and death certificate data could strengthen the MMR approach by capturing relevant individual risk factors that are not currently accounted in the current study (Hall et al., 2014). A qualitative arm of the MMR is also viable. Through this method, the researcher could gain additional themes around
the phenomenological constructs of those mothers who are at risk of PND within the home visitation program (Eastwood et al., 2014c). This then can guide and further inform the quantitative results for a more robust understanding of the phenomenon overall.

Finally, the GEE approach provides population-based estimates that are population averages. To gain an understanding at the individual neighborhood level, statistical analyses such as multilevel modeling, structural equation modeling with indirect effects, Bayesian linear regression, and spatial analysis may provide further insight to these unique neighborhoods. For example, an HLM model could be used to examine the mediation and moderation of social capital between Stability and the risk of PND. Specific statistical spatial modeling could also potentially identify specific at risk neighborhoods. This in-turn, within the MMR framework, could provide knowledge to action for those neighborhoods identified as at risk (South et al., 2012).

Conclusion

Postnatal depression impacts approximately 13% of mothers, as well as their offspring; if not treated, mothers have increased risk for recurring depressive episodes throughout their lifespans (Leigh & Milgrom, 2008; Bennett & Sylvester, 2013). Extensive research has been conducted on the individual level risk factors but only a few studies have delved into the influence of maternal neighborhood characteristics (Eastwood, 2014d). Through this study, I examined the relationships between three-month EPDS scores and structural neighborhood characteristics in at-risk women enrolled in a home visitation program. From these data, it was discovered that a statistically significant negative relationship existed between Stability and PND potential. In particular, this relationship was found to be protective against the risk of PND. This
was novel in that no other study was discovered that reported this relationship and it relates well with the social determinants of health framework in that social positioning drives mental health outcomes. This finding is significant in that it is possible for the counseling profession to intervene with at-risk women not only at the individual level, through differing therapeutic approaches (individual to group), but also at the neighborhood level (e.g., advocating for policy to increase stability). Moreover, this finding supports the continued utilization of multi-leveled research and interventions on social determinants of health because “causal chains run from macro social, political, and economic factors to the pathogenesis of disease” (Blas et al., 2008 p. 1684).
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Appendix A – Standard Hierarch of Census Geographic Entities

Source: https://www.census.gov/geo/reference/pdfs/geodiagram.pdf